Estimation of Disturbances by using Adaptive Fuzzy for SISO System

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Abstract

Estimating disturbances /unknown inputs of a system based on adaptive fuzzy output is proposed for a original Adaptive Fuzzy observer for estimating the unknown and nearly periodic input LTI SISO discrete time system. It does not involve inverting the open loop system model, Therefore it can be applied to both minimum- phase and non-minimum phase systems.However, for this approach to be exact, the parallel compensator must have almost zero gain in the frequency range of the disturbance/unknown input. The effectiveness of the proposed observer design is assessed by a numerical example including model error and measurement noises, using Matlab/ Simulink software.

Keywords- *DOB/UIOB (disturbance/ unknown input observer), Adaptive Fuzzy systems, filtering.*

I. INTRODUCTION

For a system to estimate an unknown input is a long standing issue which involves different designing and modern applications. For suppose, when a system is subjected to an undesirable disturbance, one type of approach is to destroy the unknown disturbance by building an observer for on-line estimation of disturbance for killing the effect error a control action based on the disturbance estimate can be taken. Another case is fault detection and isolation [1], [2], [9], [10].

Since the conventional DOB/UIOB configuration requires system inverse, limited application is to minimum-phase systems as it were. So as to manage non-minimum phase system, upsetting just the invertible i.e stable-zero segment of the system. To make the non-minimum phase system as minimum-phase and invertible, a parallel compensator is included.

The observer depends on the polynomial estimation to locate a rough stable reverse of the non-minimum phase systems.The relative basic observer can apply to non-minimum phase systems however just for gradually time varying disturbances .

A new UIOB is proposed for LTI, SISO systems which is minimum-phase or non-minimum phase in which system state-space model is assumed to be known. The proposed observer is as an Adaptive Fuzzy based observer. The coefficients of the filter are Adaptively updated by the least-squares algorithm with covariance reset which is very important to keep the tracking ability and for estimation of time-varying disturbances.

The basic principle is explained in Section II, and the Adaptive Fuzzy based observer is proposed for disturbance estimation is introduced in Section III. To explore the effectiveness of the proposed work a non-alphabet example is given in IV Section and conclusion in Section V.

II. CONVENTIONAL ADAPTIVE FIR FILTER DESIGN

The covarianc reset is imperative to keep the fallowing capacity and helps in eualuation of time varying disturbances.We consider a LTI SISO system. G driven by an unknown disturbance d.

$$f=Gd \qquad (1)$$

where f is outpu signal, *G* is invariable, and *d* is unspecified to be equally enclosed and "nearly periodic" input. Accordingly, by the outstanding property of LTI systems the output *f* in(1) is equivalentl to $fn+\tilde{f}\omega$, where *fn* is a course of action of sinusoidal signals of the similar frequencies $\omega_i := 2\pi i/N$, $i = 0,1,\_\ \_\ \_ ,N-1$, and $\tilde{f}\ \epsilon\ \ell 2$ records for the transient response ϵof *G* and the impact of $\tilde{d}$. Let $d_n(k) = \sum_{i=0}^{N-1} Re\left(c_i e^{j.(k.\omega i)}\right)$. At that point it is notable that $f_n(k)=\sum_{i=0}^{N-1} Re(G(e^{j\omega_i})c_i e^{j.(k\omega_i)})$.Note that f^n depends only on $G(e^{j\omega_i}), i = 0,1,\ldots,N-1$.In this manner to recover d_n,one just needs to find a filter whose TF upsets G(z) at $e^{j\omega_i}$, i= 0,1,. . . , N-1.To see this, let such a filter be Q.Then

$$(Qf)(k) = (Qf_n)(k) + (Q\tilde{f}(k) =$$

$$\sum_{i=0}^{N-1} Re(Q(\, e^{j\,\omega_i})G(e^{j\,\omega_i})\; c_i e^{j.(k.\omega i)})$$
$$+\,\tilde{y}(\mathrm{k}) \;\; +(Q\tilde{f})(\mathrm{k}) \qquad (2)$$

Theorem 1: For a TF G ,finite numbers of frequencies ω_i ,$i = 0;1;$ _ _ _,N-1,and an integer $L \geq 2N - 1$,there exists no shorts of what one FIR filter Q of arrange L with actual coefficients,such that $Q(e^{j.\omega i})G(e^{j.\omega i}) = 1$ for $i = 0,1,$ _ _ _ ,$N - 1$.

Proof: We proven this result by development and demonstrate that as long as the request of the FIR filter is set to be no less than 2N - 1,one can discover no less than one filter that fulfills the required imperatives. Let $Q(z)$ be

$$Q(z) = z^{-(2N-1)} \sum_{i=0}^{N-1} (r_i z + s_i)\, Q_I(z) \qquad (3)$$
$$Q_i(z) = \prod_{m=0, m\neq i}^{N-1} (z - \; e^{j.\omega_m})(z\text{-}e^{-j.\omega_m}) \qquad (4)$$

The novel idea we proposed here is to look for an FIR filter which alters G not under any condition frequencies however just at certain basic ones,and hence circumventing the trouble of modifying the non-minimum phase zeros. At the point when the TF of G and the time of dn are exactly known,the FIR filter Q for asymptotically recovering dn from f can be built by the system described in the proof of Theorem1.

III. ADAPTIVE FUZZY INFERENCE SYSTEMS(AFIS)

A. AFIS description

AFIS helps in understanding a compressed fuzzy system with less number of rules. It utilizations the possibility of utilitarian proportionality among a RBF neural network and AFIS[7]. RBF networks offer an professional mechanism for resembling complex nonlinear mappings from the input–output data. Based on the accuracy and speed the for a specific application the Selection of a learning algorithm is choosed.[7],[8] because they do not want to retraining whenever a new data is received.

SAFIS uses the pruning and growing RBF (GAP– RBF) [8].The AFIS algorithm consists of 2 aspects,correction of the following principle parameters and purpose of the fuzzy rules [9].

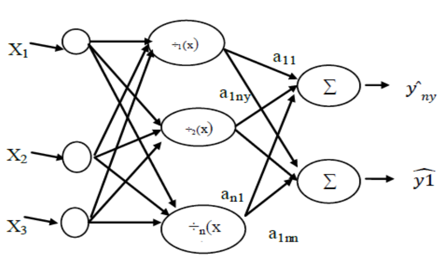

Fig 1: RBF ion Network Model

During learning AFIS uses the theory of pressure of a fuzzy rule to remove and add rules. Based on the data builds up a compact rule base and AFIS starts with no fuzzy rules.fuzzy rule is influenced by a system output in a statistical sense. The parameter modification is done using a winner rule strategy where the winner rule is defined as the limitation update is done using an EKFalgorithm and the one Closest to the input data.

It must be noted that AFIS is a truly sequential learning algorithm.RBF networks are a variety of ANN,it has one hidden layer and a linear output Fig.1,which is given by (5):

$$\hat{\boldsymbol{Y}} = \phi_{\mathbf{T}}(x)A \qquad (5)$$

The vector A is the weight's vector connecting the hidden layer to the output layer. *T(X)* is the response of the hidden layer to the input vector $X=[1,x_1,x_2,\ldots,x_n x)$where is the Gaussian function given by [10][12]:

$$\Phi(x) = \exp\left[\frac{\|x-\mu\|^2}{\sigma^2}\right] \qquad (6)$$

µ is the center's vector of the hidden neurons and α is the width of the Gaussian function.

B Description of AFIS architecture

normally,a large group of SISO nonlinear dynamic systems can be spoken to by the nonlinear discrete model with an input–output description form:

$$y(n) = f[y(n-1), y(n-2), \ldots.\, y(n-k+1)\ldots, u(n)\,, u(n-1), u(n-p+1)] \;\; K=1,2,\ldots.N_h \qquad (7)$$

Where $\boldsymbol{y}$ is a vector containing N_y system outputs, $\boldsymbol{u}$ is a vectore for N_y system inputs, $\boldsymbol{f}$ is a nonlinear vector function, k,p are the highest lags of the output and input, respectively.

$$[Y(n\text{-}1),y(n\text{-}2),\ldots..y(n\text{-}k\text{+}1),\ldots..u(n),u(n\text{-}1),u(n\text{-}p\text{+}1)],y(n) \qquad (8)$$

Selecting(7) as the fuzzy system's input –output $\mathbf{x_n}$, $\mathbf{y_n}$ at time n, the above equation can be put as:

$$Y_n = f(X_n) \qquad (9)$$

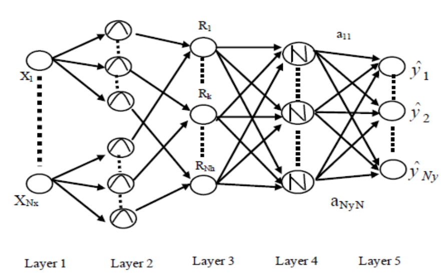

Fig 2: SAFIS Architecture.

In AFIS,the quantity of fuzzy rules N_h fluctates.At firstt,there is no fuzzy rules and after amid learning fuzzy rules are included and expelled.

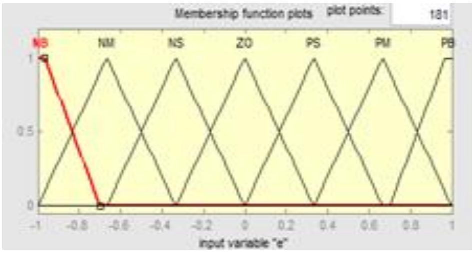

Fig 3: Membership function of error ‘e’

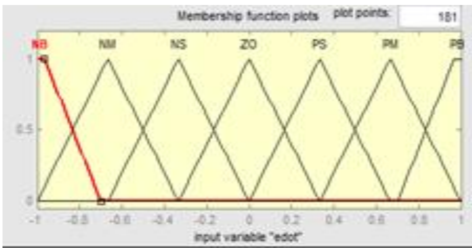

Fig 4: Membership function of change in error ‘edot’

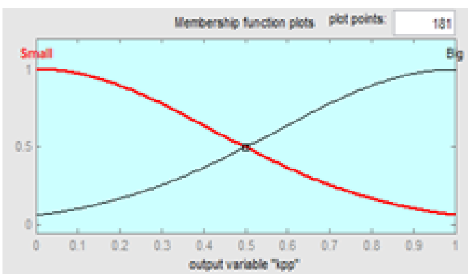

Fig 5: Membership function of ‘kpp’

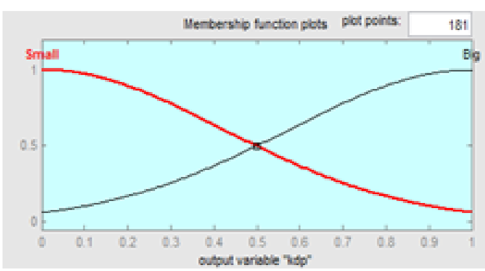

Fig 6: Membership function of ‘kdp’

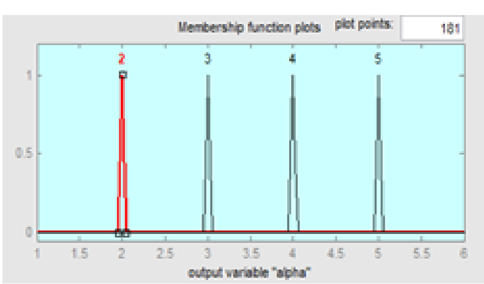

Fig 7: Membership function of ‘alpha’

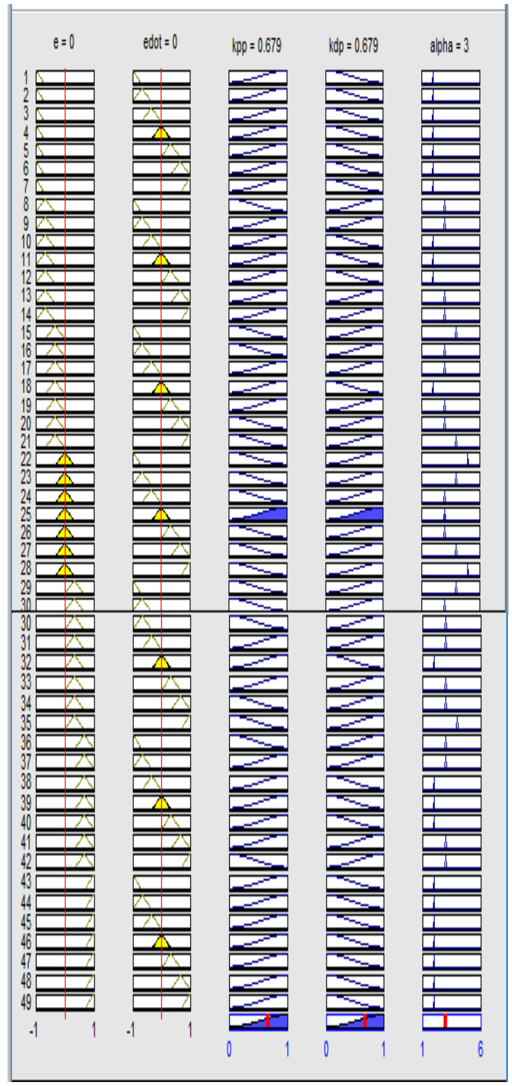

Fig 8: Fuzzy rules

IV. MATLAB SIMULATION RESULTS

Consider a 3th-order system G with the following transfer function

$$G(z) = \frac{z+2}{z^3+1.8z^2+1.07z+0.21} \qquad (10)$$

Take Note of that the system is non-minimum-phase and has an unstable zero at z=-2. The unknown input disturbance d is “nearly periodic” and set to be $d(k) = -3 + 5\cos(0.5\sqrt{k})e^{-0.1k} - 10\sin(\_\pi k/20) = d_n(k)+\tilde{d}(k)$, where the periodic component $d_n(k) = -3-10\sin(\pi k/20)$ and $\hat{d}(k)=5\cos(0.5\sqrt{k})e^{-0.1k}$. Here, every time step is interpreted as 0.025 second, and the period of dn is equal to 1 second, or 40 time steps (i.e., N = 40). The Adaptive Fuzzy Inference System (AFIS) proposed in this paper and, and with end purpose of comparison, the AFIR based observer is built to estimate d. For the AFIS, Theorem 1 is applied with L set to be 79 (i.e., $L = 2N$-1).

The leastsquares algorithm starts the parameter estimation with $\hat{\theta}(0)=0$ and P(0) =P0I= I. At the least-squares algorithm, P is reset each 50 cycles; i.e., m=50.To the best of our information, there is no efficient approach in the writing for picking the "best" weighting capacities.

The simulation results for the case(1) is there is no model error and the measured output is free of noise. The Fig.8 shows the disturbance estimates. It is having three wave forms $\hat{d}_1$ is estimation disturbance based on AFIR and $\widehat{d}_2$ is it is estimated based on Fuzzy, and input d is disturbance to the system.And the Fig.9 represents the estimation errors. The Adaptive Fuzzy filtering algorithm we suggest converges in about 50 time steps,and produces an estimate $\widehat{d}_2$ which is almost exactly equal to the true input *d* after 100 time steps. We also simulate the system with model errors and measurement noises included.

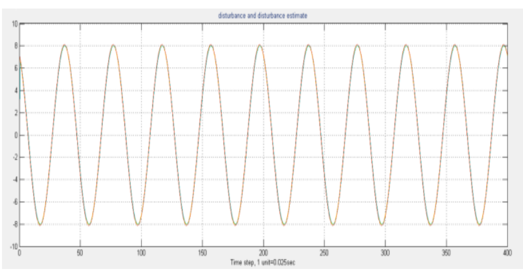

Fig 8: Disturbance and disturbance estimate

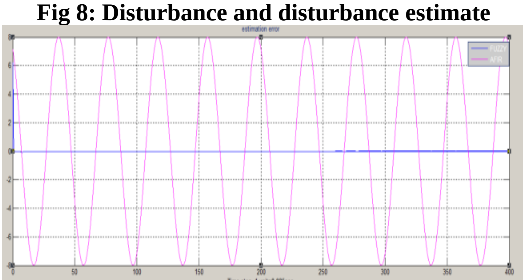

Fig 9:Case(1) wher there is no model error and no measurement noise.

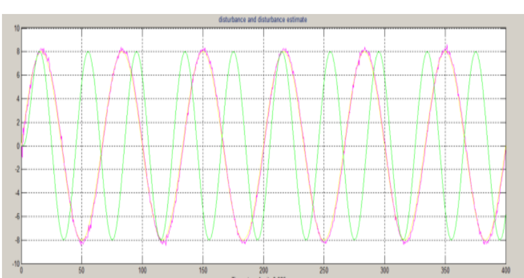

Fig 10: Disturbance and disturbance estimate

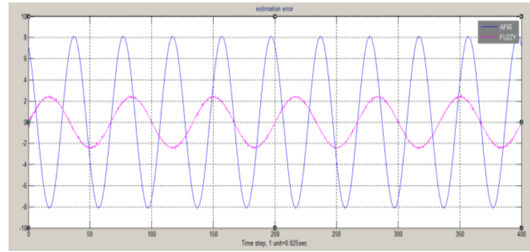

Fig 11: Case(2) where there is no model error but the output is corrupted by a stochsstic noise

Case(2) is where the output is measured with a stochastic noise v (i.e. f = Gd + v) are depicted in above fig.The amplitude of v is bounded within -0.55 as we can see from case(2).The proposed AFIS remains functional,and again produces a good disturbance estimate after about 50 times steps,but this time with a persistant estimation error,which is bounded approximately within ±1for this experiment. In comparis,the estimation error by AFIS is obviously smaller than and is about portion of that by FIR filter.

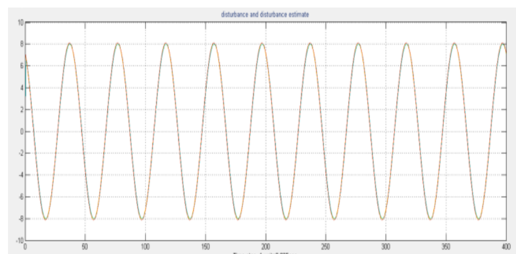

Fig 12: Disturbance and disturbance estimate

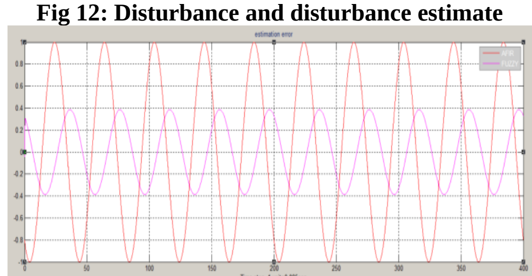

Fig 13:Case(3) where the output is free of noise but a model error is present.

And the case(3) is where a model error is presented. For this testing, we expects the genuine procedure has a transfer function *Gr*(*z*):= *G*(*z*) + Δ*G*(*z*) = (*z* + 2)/(*z*3 + 1.5*z*2 + *z* + 0.2) while the regressor is calculated base on *G*. The proposed AFIS still works even when a fairly significant model error is present. The upper figure indicates that the AFIR again converges after about 50 times steps and produces a good disturbance estimate. The estimation errors are shown in the lower figure, where we can watch that the error appears to be periodic. In comparison, we again see that the estimation error by AFIS is smaller than that by AFIR.

ACKNOWLEDGEMENT

I am grateful to extend my deep sense of gratitude to my internal guide **Sri. M. MANOHAR,Adhoc Lecturer, Dep. of EEE**,for his valuable guidance,timely advices,suggestions and support throught the duration of completing this work.

I take this opportunity to convey my sincere thanks to my parents, friends and to all those who have directly and indirectly contributed for the successful completion of my project.

V. CONCLUSION

An Adaptive Fuzzy based disturbance observer is proposed for on-line estimation of "nearly periodic" disturbances.An important advantage is that it does not involve in inverting the open system so by using this observer here achieve on-line disturbance estimation regardless of whether the system is non-minimum phase.This observer is designed by conducting numerical experiments including model errors and measurement noises and the results are provided. To certain performance measure, such as the magnitude of the estimation error are past to the extent of this work and to be resolved by further studies.

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